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Research Article

Monitoring Murder Crime in Namibia Using Bayesian Space-Time Models

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This paper focuses on the analysis of murder in Namibia using Bayesian spatial smoothing approach with temporal trends. The analysis was based on the reported cases from 13 regions of Namibia for the period 2002–2006 complemented with regional population sizes. The evaluated random effects include space-time structured heterogeneity measuring the effect of regional clustering, unstructured heterogeneity, time, space and time interaction and population density. The model consists of carefully chosen prior and hyper-prior distributions for parameters and hyper-parameters, with inference conducted using Gibbs sampling algorithm and sensitivity test for model validation. The posterior mean estimate of the parameters from the model using DIC as model selection criteria show that most of the variation in the relative risk of murder is due to regional clustering, while the effect of population density and time was insignificant. The sensitivity analysis indicates that both intrinsic and Laplace CAR prior can be adopted as prior distribution for the space-time heterogeneity. In addition, the relative risk map show risk structure of increasing north-south gradient, pointing to low risk in northern regions of Namibia, while Karas and Khomas region experience long-term increase in murder risk.

1. Introduction

Namibia is a sub-Saharan country situated on the southwestern coast of Africa and has a surface area of about 824 116 square kilometers. According to [1], the Namibian population was estimated to be around 1.8 million people, and it is expected to have an annual growth rate of about 2.6 percent. Nationally, due to the policy of national decentralization, Namibia is further demarcated into 13 administrative regions, namely, Caprivi, Erongo, Hardap, Karas, Kavango, Khomas, Kunene, Ohangwena, Omaheke, Omusati, Oshana, Oshikoto, and Otjozondjupa (see Figure 1). On the other hand, details on the regional populations, the size

Table 1: Regional statistics as per 2001 population and housing census.

Region	Population size	Area (km^2)	Density
Caprivi	79 826	14 528	5.5
Erongo	107 663	63 579	1.7
Hardap	68 249	109 651	0.6
Karas	69 329	161 215	0.4
Kavango	202 694	48 463	4.2
Khomas	250 262	37 007	6.8
Kunene	68 735	115 293	0.6
Ohangwena	228 384	10 703	21.3
Omaheke	68 039	84 612	0.8
Omusati	228 842	26 573	8.6
Oshana	161 916	8 653	18.7
Oshikoto	161 007	38 653	4.2
Otjozondjupa	135 384	105 185	1.3

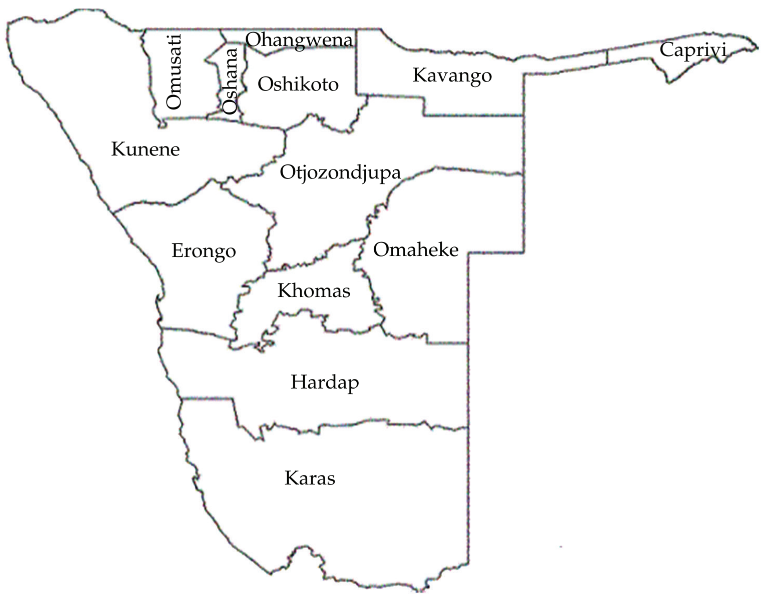

Figure 1: Regional boundary map of Namibia.

of each region in km^2, and relative population density for each region which is measured by person per km^2 as per [1] are presented in Table 1.

It follows from the above table that the biggest regions in Namibia are Karas (161215 km^2) and Kunene (115293 km^2), while the northern regions of Oshana (8653 km^2) and Ohangwena (10703 km^2) appear to be the smallest. However in contrast, Ohangwena region in particular appears to be the most populated region with a population density of 21.3 person/km^2, while Karas region is the least populated with a corresponding ratio of 0.4 person/km^2. In fact, it is important to point out that the top three most populated regions are in the north with only the central region of Khomas having a population density exceeding 5 person/km^2. This is quite expected as the northern regions accounts for about 62 percent of the total population size.

1.1. The Problem of Crime

Namibia is one of the developing countries in the sub-Saharan Africa, specifically in the Southern African Development Community (SADC) region with a high crime rate. In general, according to [2], developing countries tends to have quite high rates of crimes due to unfavorable prevailing socioeconomic conditions, a high unemployment levels and the lack of organized police and justice systems among others. The result of a study on South Africa's position in Africa's crime ranking by [3], based on the International Criminal Police Organization (Interpol) African crime statistics of 1997 indicates that out of the nine sub-Saharan countries such as Côte d'Ivoire, Ethiopia, Ghana, Namibia, South Africa, Swaziland, Tanzania, and Zimbabwe that provided data on the cases of murder, Namibia has the second highest cases of murder per capita of about 0.480 per 1000 people, just below South Africa (0.592 per 1000 people) and above Swaziland (0.190 per 1000 people).

In addition, the rate of murder in Namibia in 2006 was 0.168 per 1000 people which puts Namibia among the top 6 countries in the world with the highest murder rates and three places below another SADC country in the form of South Africa (0.496 per 1000 people) according to [4]. At national level, the Namibian Economic Policy Research Unit (Nepru), in its quarterly economic report of 2002, reveals that in 2000 the government of Namibia (GRN) contributes 10 percent of the total government budget, about N$1368 million Namibian dollar on security services. Besides government spending, individuals spend a further N$343 million on property insurance, N$433 million on security installations, and a further N$274 million on private security services. In addition, the cost related to crime in Namibia in 2002 amounts to not less than N$2650 million representing about 11 percent of the country gross domestic product (GDP) and doubles the spending in the year 2000.

These statistics and the overall standing of Namibia in the world and the regional crime ranking appear quite alarming. The belief that crime can be reduced through good management is quite essential to the 21st century policing, as is the use of new information technology and proper analytical procedures in the initiations of proper planning mechanism and better resource allocations. In particular, research conducted in the context of crime and risk assessments in Namibia is quite minimal and poorly documented, thus its quality is often questionable. Therefore, the findings of this paper can play an important role in the understanding of the underlying factors contributing to unusual high level of regional risk of murder in Namibia so that proper and timely interventions can be initiated. In addition, it can also be used in improving policing in general through proper allocation of the millions spent by the government and other resources to the relevant areas with increasing risk of murder.

The paper, therefore, places emphasis on the application of the fully Bayesian approach in monitoring changes in the risk of murder in the 13 regions of Namibia over time. In particular, the focus is on a comprehensive evaluation of uncertainty in unobserved random effects contributing to the variation in the relative risk of murder across the regions over time. As per [5] in a criminological setting, crime is viewed as an event that can be described by various topological dimensions such as space, time, offenders, and so on. Although these topological dimensions can be extended accordingly, it is imperative to point out that the space and time components form the core dimensions in this paper.

2. Data and Methods

2.1. Data

The paper makes use of the statistics on the reported cases of murder from 2002–2006 period which were collected from the records of the uniform crime reports (UCRs) in the Department of Crime Information Unit (CIU) of the Namibian Police (NAMPOL). The crime statistics from the UCR in particular are recorded on an annual basis, as the UCR is a summary type-based recording system in which annual crime data are regionally aggregated. It is, however, important to point out here that generally the statistics on the cases of crimes in Namibia are not entirely recorded for statistical analysis purposes but rather are primarily collected for use in annual publications such as annual police reports, budget preparations as well as in the administration and management of operations for law enforcement agencies. As such these annual statistics were used in this paper as they are the only available comprehensive data sets on the murder situation in Namibia during the study period. However, for comparison purposes these statistics were further complemented by regional population projections from the Central Bureau of Statistics (CBS) in the National Planning Commission (NPC).

2.2. Methods

An adaptation of the Fully Bayesian (FB) model allowing for smooth integration of prior information into posterior distribution of the regional relative risk of murder is used. Let o_{rt} and e_{rt} be observed and expected cases of murder from region r during the time period t and λ_t the rate of murder during the time period t which is estimated by $\widehat{\lambda}_t = \sum_r o_{rt} / \sum_r n_{rt}$, where n_{rt} is the respective regional population at risk [6]. Since the reference population is not readily available, the e_{rt} was calculated based on the regional population at risk as $e_{rt} = \widehat{\lambda}_t n_{rt}$. Therefore, the regional specific rate of murder during the time period t is then denoted by $\widehat{\lambda}_{rt}$ such that for $o_{rt} \mid \widehat{\lambda}_{rt}, e_{rt} \sim Po(\widehat{\lambda}_{rt} e_{rt})$, a flexible prior for the log relative risk given by the normal prior distribution is suggested. This is in the form:

$$\log(\lambda_{rt}) = \log(n_{rt}) + \beta_0 + \theta_{rt}, \quad r = 1, 2, \ldots, R, \; t = 1, 2, \ldots, T, \tag{2.1}$$

where $\log(n_{rt})$ is the model offset accounting for population sizes, β_0 is the overall level of the relative risk of murder, θ_{rt} measures the unknown specific space-time regional level random effects, $\theta_{rt} \sim N(0, \sigma^2)$, where σ^2 is the hyper parameter measuring variation between space-time regional log relative risk of murder. In the absence of prior information on parameters of interest, noninformative prior can be assigned. In addition, prior distribution associated with unknown specific space-time regional level random effect (θ_{rt}) can be expressed as an independent prior, where unstructured heterogeneity in the relative risk estimate is considered or as a space-time structured prior in which geographical location of a region is important. This is the idea of [7] which proposed adjustment to the Bayesian model split information on regional specific relative risk into two groups of random effects representing spatial dependence heterogeneity or clustering heterogeneity and uncorrelated heterogeneity. The paper refers to these random effects as the space-time structured heterogeneity (u_{rt}) and unstructured heterogeneity (v_{rt}). The extended BYM model is in the form:

$$\log(\lambda_{rt}) = \log(n_{rt}) + \beta_0 + u_{rt} + v_{rt}. \tag{2.2}$$

This model has been extensively studied and applied in many problem solving situation see [8–10] amongst others. Assessment of the time effect is also important as monitoring changes in the regional relative risk of murder over time is one of the core aspects of the paper. This component is conventionally incorporated into the model as a time trend (tt_t). Alternatively, other random effect parameters and covariate effects of interest can also be incorporated into the model. Overall, the variables of interest are regional clustering, time, space and time interaction, and the population density. The model takes the form:

$$\log(\lambda_{rt}) = \log(n_{rt}) + u_{rt} + v_{rt} + \mathrm{tt}_t + \gamma_{rt} + \beta_0 + \beta_1 x_{rt}, \tag{2.3}$$

where γ_{rt} is the random effect representing the space and time interaction, while β_1 is the effect of population density. The above model is referred to as the space-time interaction model, see [10, 11]. The model is completed by carefully choosing proper prior and hyper prior distributions for model parameters. In particular, the space-time conditional autoregressive prior (CAR prior) was used to account for potential space-time regional correlation. This takes the form $[u_{rt} \mid u_{lt} : r \neq l, \tau_u^{-1}] \sim \mathrm{CAR}.N(\overline{u}_{rt}, \tau_u^{-1})$, $r, l = 1, 2, \ldots, R$, where $\overline{u}_{rt} = \sum_t (\sum_l u_{lt} w_{rlt} / \sum_l w_{rlt})$, and w_{rlt} is a composition matrix of weights constructed from the space-time regional adjacency matrix and defined as

$$w_{rt} = \begin{cases} 1 & \text{if region } r \text{ is adjacent to region } l \\ 0 & \text{otherwise.} \end{cases} \tag{2.4}$$

On the other hand, the unstructured heterogeneity component is introduced to absorb the independence assumption not satisfactorily defined in terms of the structure of the space-time structured random effect, see [11–14]. Hence, an independent normal prior distribution is assigned to v_{rt}, say $v_{rt} \mid \tau_v^{-1} \sim \mathrm{indep}.N(0, \tau_v^{-1})$. The degree of variation in the random effects are measured by precision parameters τ_u and τ_v which are inversely proportional to the variance of the two random effect, that is, $\sigma_u^2 = \tau_u^{-1}$ and $\sigma_v^2 = \tau_v^{-1}$. This result in an inverse gamma prior distribution conjugated to the normal distribution for the respective σ_ξ^2, $\xi \in (u, v)$.

For the time trend effect (tt_t), the intrinsic Gaussian prior distribution is assumed. However, for one-dimensional space, this prior has been shown by [12–14] to reduce to a Gaussian random walk of the form $\mathrm{tt}_t \mid \tau_{\mathrm{tt}}^{-1} \sim .N(0, \tau_{tt}^{-1})$ for $t = 1$ and $\mathrm{tt}_t \mid \mathrm{tt}_{t-1}, \tau_{\mathrm{tt}}^{-1} \sim .N(\mathrm{tt}_{t-1}, \tau_{\mathrm{tt}}^{-1})$ for $t = 2, 3, \ldots, T$. Other prior distributions are $\gamma_{rt} \mid \tau_\gamma^{-1} \sim .N(0, \tau_\gamma^{-1})$ and $\beta_1 \mid \tau_{\beta_1}^{-1} \sim .N(0, \tau_{\beta_1}^{-1})$ for the interaction and the population density effect, while a flat prior is assigned to β_0. Similarly, an inverse gamma prior distribution is assumed for σ_{tt}^2, σ_γ^2 and $\sigma_{\beta_1}^2$. Therefore, it can be deduced from the above formulas that the analysis of regional relative risk of murder involves a trade-off between the estimates statistical stability and regional precision.

Inference on posterior estimates of the relative risk is done via the Gibbs sampling algorithm [15], while convergence is monitored using the Gelman and Rubin method [16] with minor correction by [17] complemented with monitoring sequence of variance and that within variance sequence which should stabilize with increasing number of iterations [17] and also visual inspection of the sample trace plots of relevant parameters [10].

Table 2: Posterior mean estimates of parameters from the FB model.

Nodes	Mean	(95% CI)
$\exp(\beta_0)$	0.889	(0.720; 1.083)
$\exp(\beta_1)$	1.010	(0.994; 1.026)
σ_{β_1}	0.044	(0.014; 0.110)
σ_{tt}	0.079	(0.016; 0.253)
σ_u	0.683	(0.475; 0.869)
σ_v	0.089	(0.017; 0.281)
σ_γ	0.074	(0.016; 0.240)

3. Application and Results

The initial approach is to fit the space-time interaction model (2.3). In the model setup, prior distributions discussed in Section 2.2 are assigned to the respective parameters of interest. In both prior distributions, we have assigned a gamma hyper prior distribution to the precision parameters taking the value $\tau_\xi \sim \Gamma(0.5, 0.0005)$ and noting that $\sigma_\xi^2 = 1/\tau_\xi$ [10, 18]. The posterior estimates of the parameters of interest are then achieved by running two chains from dispersed starting values in WinBUGS, where a reasonable convergence was reached after 344,000 iterations. Therefore, in this case the first 344,000 iterations were discarded as burn-in period. In addition, the question of how much iteration to run after convergence is attained before terminating is always a tricky one as there is no standard guideline. However, the rule of thumb is to terminate iterative process after the estimated parameters have reached a Markov chain standard error of less than 5%.

The Markov chain standard error of the mean estimate of parameters according to [18] is the standard deviation of the difference between the mean of the sampled values and the true posterior mean for the derivation of these errors. Therefore in order to estimate the parameters of interest with high degree of precision, Markov chain errors should be as low as possible. This scenario results in an additional 30600 iterations on which inferences about the parameters of interest were based. The resulting posterior mean estimates for β_0, β_1, σ_{β_1}, σ_{tt}, σ_u, σ_v, and σ_γ and their 95% credible intervals are presented in Table 2. Note that we are reporting the standard deviations σ_ξ rather than the precision parameters τ_ξ as they are more easily interpretable.

The result from the table shows that the rate of the overall level of the relative risk when no random or covariate effect parameters are in the model is 0.889. Most of the variation in the relative risk of murder is due to space-time regional clustering as it has the highest standard deviation ($\sigma_u = 0.683$). It is also noteworthy to point out that although there is a unit increase in the relative risk of murder when population density is added to the model, evaluation of its overall contribution to total variation in the relative risk of murder is quite minimal ($\sigma_{\beta_1} = 0.044$). These findings are consolidated by running model selection process supplemented with corresponding model fit. In this case, the reference model is taken to be a simple model with a time trend (tt_t) component as it forms an integral part of the analysis and then expand the model by incorporating the rest of the variables. In fitting these models, we assume a good representation of central location by the posterior mean in describing posterior distribution of the estimated parameters. Furthermore, since the model parameters are estimated using MCMC methods, a deviance information criterion (DIC) was used in choosing the most parsimonious model based on the model fit and complexity [19].

Table 3: Results of the model fit and selection criterion.

Model	Variables	DIC	ΔDIC
1	(tt_t)	838.579	
2	(tt_t, u_{rt})	437.690	−400.889
3	(tt_t, v_{rt})	438.556	0.866
4	$(\mathrm{tt}_t, u_{rt}, v_{rt})$	437.244	−1.312
5	$(\mathrm{tt}_t, u_{rt}, v_{rt}, \gamma_{rt})$	437.021	−0.223
6	$(\mathrm{tt}_t, u_{rt}, v_{rt}, \gamma_{rt}, \beta_1 x_{rt})$	436.642	−0.379

Table 4: Posterior mean estimates of the parameters from model 2.

Nodes	Mean	(95% CI)
$\exp(\beta_0)$	0.936	(0.724; 1.126)
σ_{tt}	0.082	(0.016; 0.281)
σ_u	0.744	(0.605; 0.904)

Comparison of the respective model fit by the DIC criterion based on a further 10,000 iterations after convergence for each model is shown in Table 3. In the table, ΔDIC is the change in the deviance with respect to the deviance of the preceding model, with −ΔDIC indicating an improved fit on the current model. Generally the best model fit is given by the model that minimizes the DIC; however, [20] suggests a significant difference in the model fit for $\Delta\mathrm{DIC} \geq 4$. The result from the table shows that there is a significant improvement in the model fit when the space-time structured heterogeneity is added to the reference model (model 2, $\Delta\mathrm{DIC} = -400.889$); however, adding more variables such as unstructured heterogeneity (model 3), space and time interaction term (model 5), and the effect of population density (model 6) does not further improve the model fit. This confirms the findings from Table 2, where space-time regional clustering explained much of the variation in the relative risk of murder.

Overall, based on the above results it is reasonable to fit model 2 alone in order to fully evaluate the effect of space-time structured heterogeneity on the relative risk of murder. The posterior mean estimate of the parameters obtained from fitting model 2 and their 95% credible intervals are presented in Table 4. It is, therefore, evident from this table that the estimates are fairly close to those found in Table 2. In addition, model 2 provides tighter credible intervals for σ_u which can be attributed to the fact that σ_u has absorbed much of the space-time variation, and hence it provides more information on the space-time regional relative risk of murder.

The distribution of posterior mean estimates for the space-time structured heterogeneity (u_{rt}) into the study regions over time is shown in Figure 2. In this figure, each map represents the individual time periods, while tercile legends were used to provide an amply coverage of the measurements. Most of the regional random variation (unstructured heterogeneity) as expected has been well eliminated with the structured heterogeneity becoming more prominent over time. The space-time structured heterogeneity is now showing an estimated regional block of the relative risk with increasing northsouth gradient structure. This effect as indicated from Table 4 is prominently represented as it is shown to account for over 55% coverage of the space-time regions with a positive correlated heterogeneity. Also, the overall contribution of the time trend component to total variation in the relative risk of murder is quite minimal ($\sigma_{\mathrm{tt}} = 0.082$). The time series plot for the posterior

Figure 2: Distribution of the posterior mean value for the space-time structured heterogeneity (u_{rt}) onto study regions.

mean estimates of the time trend component displayed in Figure 3 indicates that although there is an overall steady increase in the temporal trend over time, the trend appears to be very smooth.

Similarly, the distribution of the posterior mean estimate of the regional space-time relative risk into components of the relative risk of murder is shown in Figure 4, where a 3 classification, namely, high-(dark colour), medium-(light grey), and low-(white colour) risk classes were used.

The effect of regional clustering is particularly well articulated in the maps where a clear regional block of increasing north-south gradient in the relative risk of murder is visible. In particular, regions of Karas and Khomas have been consistently classified as high-risk areas over time; however, although the regions of Omaheke and Hardap were only classified as high-risk areas in 2003, 2004, and 2006, they need to be closely monitored.

4. Sensitivity Analysis

The normal CAR model used in Section 2.2 may be restrictive and not robust to changes in the specification of the spatial effects. Therefore, a limited sensitivity analysis is performed to investigate changes in the results by specifying a Laplace (double exponential) CAR model for the spatial effect on the same lines as the CAR normal model. Similarly, two prior distributions for the intercept term β_0 in the form of an improper noninformative flat prior and a proper normal distribution prior were also considered. This test is particularly important as according to [21, 22] posterior distribution has a tendency to either overestimate

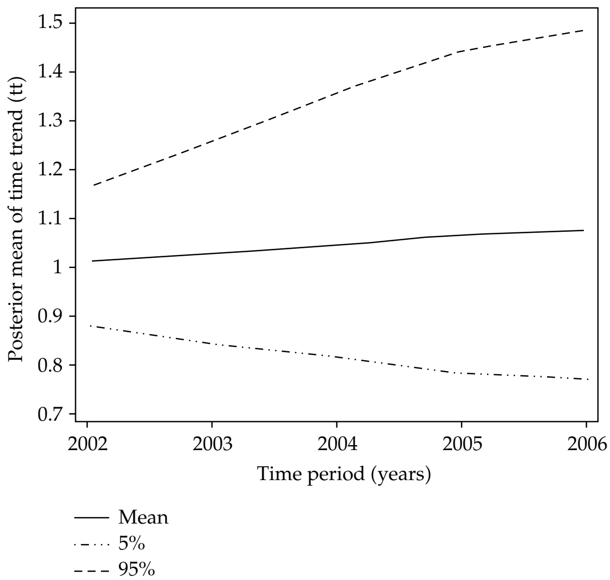

Figure 3: Time series plot for posterior mean estimates of the time trend with 95% CI.

or underestimate various aspect of the true posterior uncertainty more especially with respect to prior specification.

Here we run two chains with multiple starting values, whereby the starting values for chain 1 were fixed (i.e., a reference chain) with those of chain 2 adjusted accordingly. The starting values for the reference chain will be denoted by tt[0] as a 1×5 vector and $u[0]$ as a 5×13 vector of zero values for the time trend (tt_t) and the space-time structured heterogeneity (u_{rt}), while $\tau_\xi = 1$ (i.e., $\tau_{\mathrm{tt}} = \tau_u = 1$) as starting value for the respective precision parameters. Similarly, we assign the same notation to the starting values for chain 2, which control the degree of overdispersion between the starting values. The test is conducted for three values of 10% decrease in the precision parameter of chain 2 at each time, namely, 0.1, 0.01, and 0.001. The resulting outcome of the test at each time is presented in Table 5. The burn in period for parameter estimation ranges widely between 3000 and 140000 iterations with the chains running longer in the case of the flat prior distribution on β_0.

The result shows that under each prior distribution for u_{rt}, the posterior estimates of the model parameters are fairly close irrespective of prior distributions for β_0 and the starting values. In contrast, changes in the prior distribution for u_{rt} result in an increase of about 0.176 in the posterior estimates of σ_u under Laplace CAR prior distribution. Overall, although the posterior mean estimates of the model parameters are slightly different under more significant decimal digits, it is reasonable to conclude that the model is fairly stable and immune to changes in the starting values and prior distribution for β_0 as these differences are not substantially large enough. Nevertheless, since the prior distributions for the space-time structured heterogeneity result in an inconclusive outcome as they provide varying posterior mean estimates of the standard deviation of the estimated parameters, either one of them can be equally adopted.

5. Discussion

The issue of the seriousness of the crime situation in Namibia over the years cannot be highly emphasized. Although, government and other relevant sectors such as the Namibian police,

Figure 4: Crime maps of the posterior mean estimates of the relative risk (λ_{rt}) of murder.

municipalities, security companies, and individuals amongst others have spent considerable efforts and resources on measures pertaining to the reduction of murder in the country, less effort on understanding the contributing factors to the increase in the relative risk of crime has been achieved. In particular, the reported rate of murder per capita which put Namibia among the highest nation in the world needs a further understanding if it is to be reduced or managed to a lesser level. In doing so, the paper adopts an application of the FB approach, which comprehensively evaluates uncertainty in the unobserved random effects contributing to the variation in the space-time regional relative risk of murder. The evaluated random effects include regional clustering (space-time structured heterogeneity), unstructured heterogeneity, time, space and time interaction, and population density.

The result shows that most of the variation in the relative risk of murder is due to regional clustering, while the effect of population density and the time trend was insignificant as their overall contribution to the total variation in the relative risk was minimal. Furthermore, the space-time regional distribution of the posterior mean estimate for the space-time structured heterogeneity shows an estimated space-time regional block of relative risk with increasing north-south gradient structure. This is, however, expected given the dominant contribution of the space-time structured heterogeneity to the total variation in the relative risk of murder over time. In addition, the resulting space-time regional classification by the components of the relative risk points to the northern part of Namibia being a low-risk area for murder over time as most of the northern regions were consistently classified into the low-risk class. In contrast, regions of Karas and Khomas are showing long-term increase in the risk of murder over the study period.

Table 5: Posterior mean estimate of the model parameters and the corresponding 95% CI under varying starting values and prior distributions for β_0 and u_{rt}.

Prior for β_0	Starting values	Parameter	Prior for u_{rt} Intrinsic CAR prior Mean	(95% CI)	Laplace CAR prior Mean	(95% CI)
flat( )	tt[1], $u[1]$, $\tau_\xi = 0.1$	$\exp(\beta_0)$	0.936	(0.724, 1.126)	0.947	(0.787, 1.116)
		σ_{tt}	0.082	(0.016, 0.281)	0.073	(0.016, 0.225)
		σ_u	0.744	(0.605, 0.904)	0.920	(0.809, 1.043)
	tt[2], $u[2]$, $\tau_\xi = 0.01$	$\exp(\beta_0)$	0.962	(0.745, 1.217)	0.949	(0.787, 1.120)
		σ_{tt}	0.091	(0.016, 0.324)	0.069	(0.016, 0.213)
		σ_u	0.744	(0.605, 0.903)	0.920	(0.810, 1.043)
	tt[3], $u[3]$, $\tau_\xi = 0.001$	$\exp(\beta_0)$	0.941	(0.684, 1.154)	0.970	(0.792, 1.176)
		σ_{tt}	0.089	(0.016, 0.312)	0.079	(0.016, 0.263)
		σ_u	0.744	(0.606, 0.904)	0.920	(0.809, 1.042)
$N(0, 1.0^{-5})$	tt[1], $u[1]$, $\tau_\xi = 0.1$	$\exp(\beta_0)$	0.947	(0.727, 1.156)	0.950	(0.766, 1.146)
		σ_{tt}	0.085	(0.016, 0.291)	0.081	(0.016, 0.250)
		σ_u	0.744	(0.606, 0.904)	0.920	(0.809, 1.043)
	tt[2], $u[2]$, $\tau_\xi = 0.01$	$\exp(\beta_0)$	0.947	(0.721, 1.164)	0.956	(0.752, 1.182)
		σ_{tt}	0.087	(0.016, 0.299)	0.089	(0.016, 0.312)
		σ_u	0.744	(0.606, 0.904)	0.920	(0.809, 1.043)
	tt[3], $u[3]$, $\tau_\xi = 0.001$	$\exp(\beta_0)$	0.953	(0.751, 1.169)	0.957	(0.757, 1.220)
		σ_{tt}	0.083	(0.016, 0.277)	0.080	(0.016, 0.265)
		σ_u	0.743	(0.606, 0.903)	0.921	(0.809, 1.044)

These results agree with the findings of [1], where it was found that northern regions are losing people to urban areas of Khomas, Karas, and Erongo regions in search of job opportunities and better standard of living as a result of industrialization in these regions. However, not everyone ended up to the job market nor acquired better standard of living and as such most people tend to life of crime. The risk of murder increases with high crimes such as robberies and housebreaking, and it creates a burden in the ability of the local police to properly address and manage cases of murder in an ever increasing urban population due to the lack of resources and poor training amongst others [23]. Hence, the continuous increase in the relative risk of murder in the above regions has policy and economic implications as the government's apparent inability to curb this problem becomes a reality. In general, however, crime reduces commercial investments in the country, as investors will be reluctant to invest in commercial and industrial property if their safety is not guaranteed. Therefore, when policy and decision makers in the country are formulating policies and strategies aimed at reducing the rate of murder, they should also focus on the neighboring regions as the results show a dependency in the relative risk of murder in a particular region to the neighboring regions.

Finally, the outcome of the sensitivity test shows that although the posterior mean estimates of the model parameters are slightly different under more significant decimal digits, the model is fairly stable and immune to the changes in both starting values and the prior distribution for β_0 as these differences are not substantially large enough. Nevertheless, since the Intrinsic and Laplace CAR prior gives inconclusive outcome as they provide varying posterior mean estimates of the standard deviation of the estimated parameters, we recommend that any one of them can be adopted as prior distributions for the space-time structured heterogeneity.

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